```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.metrics import classification_report, confusion_matrix
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
from tensorflow.keras.optimizers import Adam, RMSprop, SGD
from tensorflow.keras.callbacks import EarlyStopping
import optuna  # For hyperparameter optimization
```

```
# ======================
# Step 1: Data Preprocessing
# ======================
def load_and_preprocess_data():
    # Load dataset (replace with your actual data loading)
    data = pd.read_csv('/content/teleconnect.csv')

    # Handle missing values in TotalCharges (empty strings -> NaN -> median)
    data['TotalCharges'] = pd.to_numeric(data['TotalCharges'], errors='coerce')
    data['TotalCharges'].fillna(data['TotalCharges'].median(), inplace=True)

    # Define features and target
    X = data.drop(['customerID', 'Churn'], axis=1)
    y = data['Churn'].map({'Yes': 1, 'No': 0})

    # Preprocessing pipeline
    numeric_features = ['tenure', 'MonthlyCharges', 'TotalCharges']
    categorical_features = ['gender', 'Partner', 'Dependents', 'PhoneService',
                          'MultipleLines', 'InternetService', 'OnlineSecurity',
                          'Contract', 'PaymentMethod']

    preprocessor = ColumnTransformer(
        transformers=[
            ('num', StandardScaler(), numeric_features),
            ('cat', OneHotEncoder(drop='first'), categorical_features)
        ])

    X_processed = preprocessor.fit_transform(X)
    return X_processed, y

X, y = load_and_preprocess_data()
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

```
<ipython-input-21-666a012f2eae>:10: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on whi

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' o


  data['TotalCharges'].fillna(data['TotalCharges'].median(), inplace=True)
```

```
# ======================
# Step 2: Baseline ANN Model
# ======================
def create_baseline_model(input_dim):
    model = Sequential([
```

```
        Dense(64, activation='relu', input_shape=(input_dim,)),
        Dropout(0.3),
        Dense(32, activation='relu'),
        Dense(1, activation='sigmoid')
    ])
    model.compile(optimizer=SGD(learning_rate=0.01),
                  loss='binary_crossentropy',
                  metrics=['accuracy', tf.keras.metrics.Recall()])
    return model

baseline_model = create_baseline_model(X_train.shape[1])
history = baseline_model.fit(X_train, y_train,
                             epochs=50,
                             batch_size=32,
                             validation_split=0.2,
                             verbose=1)

# Evaluate baseline
y_pred = (baseline_model.predict(X_test) > 0.5).astype(int)
print("=== Baseline Model (SGD) ===")
print(classification_report(y_test, y_pred))
```

```
=== Baseline Model (SGD) ===
              precision    recall  f1-score   support

           0       0.84      0.91      0.88      1036
           1       0.68      0.54      0.60       373

    accuracy                           0.81      1409
   macro avg       0.76      0.72      0.74      1409
weighted avg       0.80      0.81      0.80      1409
```

```
# Step 3: Optimized Models
# ======================
# Adam Optimizer
def create_adam_model(input_dim):
    model = Sequential([
        Dense(64, activation='relu', input_shape=(input_dim,)),
        Dropout(0.3),
        Dense(32, activation='relu'),
        Dense(1, activation='sigmoid')
    ])
    model.compile(optimizer=Adam(learning_rate=0.001),
                 loss='binary_crossentropy',
                 metrics=['accuracy', tf.keras.metrics.Recall()])
    return model

adam_model = create_adam_model(X_train.shape[1])
adam_history = adam_model.fit(X_train, y_train,
                             epochs=50,
                             batch_size=32,
                             validation_split=0.2,
                             verbose=0)  # Silent training

# RMSprop Optimizer
def create_rmsprop_model(input_dim):
    model = Sequential([
        Dense(64, activation='relu', input_shape=(input_dim,)),
        Dropout(0.3),
        Dense(32, activation='relu'),
        Dense(1, activation='sigmoid')
    ])
    model.compile(optimizer=RMSprop(learning_rate=0.001),
                 loss='binary_crossentropy',
                 metrics=['accuracy', tf.keras.metrics.Recall()])
    return model

rmsprop_model = create_rmsprop_model(X_train.shape[1])
rmsprop_history = rmsprop_model.fit(X_train, y_train,
                                   epochs=50,
                                   batch_size=32,
                                   validation_split=0.2,
                                   verbose=0)
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/layers/core/dense.py:87: UserWarning: Do not pass an `input_shap
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

```
# ======================
# Step 4: Hyperparameter Tuning with Optuna
# ======================
def objective(trial):
    # Define hyperparameters to optimize
    params = {
        'learning_rate': trial.suggest_float('learning_rate', 1e-4, 1e-2, log=True),
        'units': trial.suggest_categorical('units', [32, 64, 128]),
        'dropout_rate': trial.suggest_float('dropout_rate', 0.1, 0.5)
```

```
    }

    model = Sequential([
        Dense(params['units'], activation='relu', input_shape=(X_train.shape[1],)),
        Dropout(params['dropout_rate']),
        Dense(params['units']//2, activation='relu'),
        Dense(1, activation='sigmoid')
    ])

    model.compile(optimizer=Adam(learning_rate=params['learning_rate']),
                  loss='binary_crossentropy',
                  metrics=['accuracy'])

    # Early stopping to prevent overfitting
    early_stopping = EarlyStopping(monitor='val_loss', patience=5)

    history = model.fit(X_train, y_train,
                        epochs=50,
                        batch_size=32,
                        validation_split=0.2,
                        callbacks=[early_stopping],
                        verbose=0)

    # Return validation accuracy
    return history.history['val_accuracy'][-1]

# Run optimization (comment out if short on time)
study = optuna.create_study(direction='maximize')
study.optimize(objective, n_trials=10)  # Reduce trials for faster execution

# Best model from Optuna
best_params = study.best_params
optimized_model = Sequential([
    Dense(best_params['units'], activation='relu', input_shape=(X_train.shape[1],)),
    Dropout(best_params['dropout_rate']),
    Dense(best_params['units']//2, activation='relu'),
    Dense(1, activation='sigmoid')
])
optimized_model.compile(optimizer=Adam(learning_rate=best_params['learning_rate']),
                        loss='binary_crossentropy',
                        metrics=['accuracy', tf.keras.metrics.Recall()])
optimized_model.fit(X_train, y_train, epochs=50, batch_size=32, verbose=0)
```

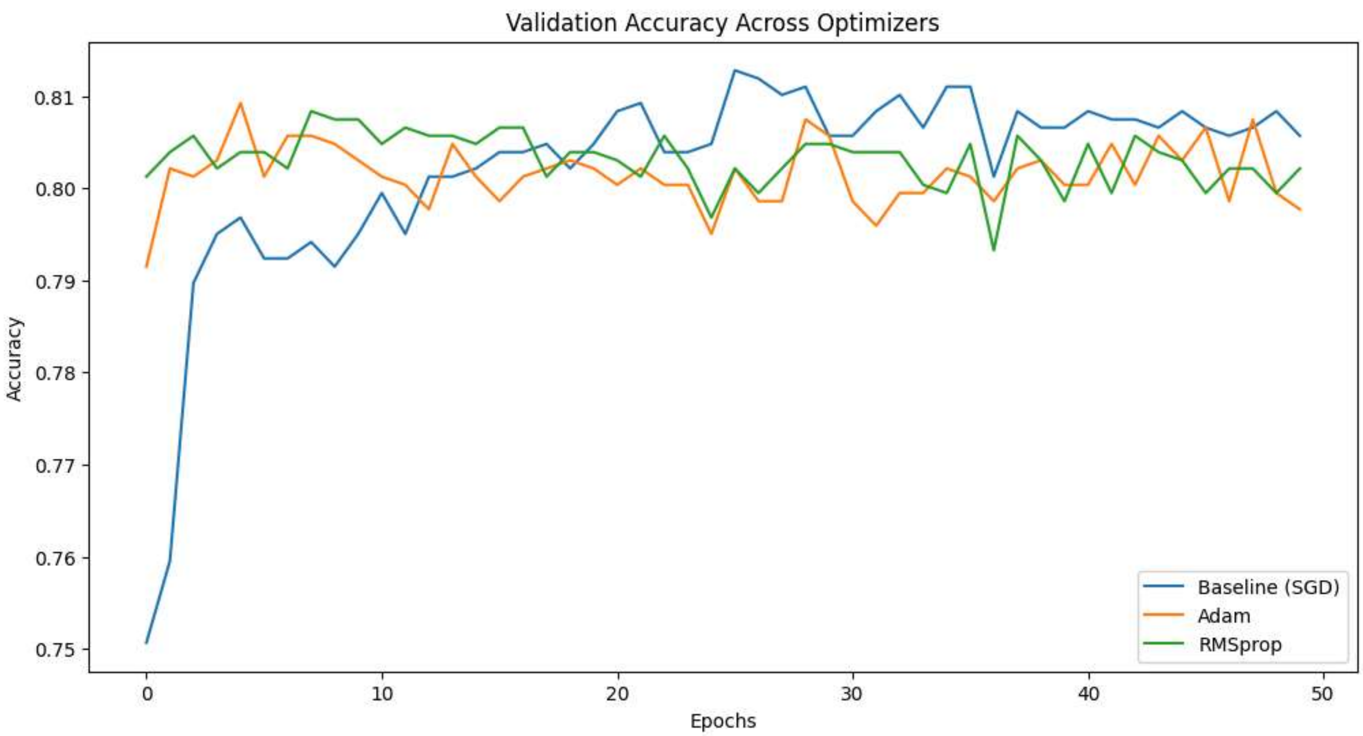
```
21:53:58,058] A new study created in memory with name: no-name-c5869c47-44fd-4308-bcbe-fd5cdd4d32ca
21:54:24,573] Trial 0 finished with value: 0.8047915101051331 and parameters: {'learning_rate': 0.00012270808614132
21:54:35,777] Trial 1 finished with value: 0.8030168414115906 and parameters: {'learning_rate': 0.00390581332174277
21:54:48,955] Trial 2 finished with value: 0.7994676232337952 and parameters: {'learning_rate': 0.00502844473559733
21:54:59,983] Trial 3 finished with value: 0.8030168414115906 and parameters: {'learning_rate': 0.00098402011113748
21:55:06,741] Trial 4 finished with value: 0.8003548979759216 and parameters: {'learning_rate': 0.00173963652954666
21:55:26,510] Trial 5 finished with value: 0.8074533939361572 and parameters: {'learning_rate': 0.00023630080449714
21:55:35,796] Trial 6 finished with value: 0.8021295666694641 and parameters: {'learning_rate': 0.00111246103762283
21:55:40,781] Trial 7 finished with value: 0.8039041757583618 and parameters: {'learning_rate': 0.00662538437987054
21:55:52,477] Trial 8 finished with value: 0.8003548979759216 and parameters: {'learning_rate': 0.00076535751205193
21:56:03,249] Trial 9 finished with value: 0.8030168414115906 and parameters: {'learning_rate': 0.00124432386283567
lbacks.history.History at 0x7c8131f1f090>
```

```
# =====================
# Step 5: Evaluation & Comparison
# =====================
def evaluate_model(model, X_test, y_test, name):
    y_pred = (model.predict(X_test) > 0.5).astype(int)
    print(f"\n=== {name} ===")
    print(classification_report(y_test, y_pred))
    return classification_report(y_test, y_pred, output_dict=True)


# Compare all models
baseline_report = evaluate_model(baseline_model, X_test, y_test, "Baseline (SGD)")
adam_report = evaluate_model(adam_model, X_test, y_test, "Adam Optimizer")
rmsprop_report = evaluate_model(rmsprop_model, X_test, y_test, "RMSprop Optimizer")
optimized_report = evaluate_model(optimized_model, X_test, y_test, "Optimized (Optuna)")
```

```
45/45 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step

=== Baseline (SGD) ===
              precision    recall  f1-score   support

           0       0.84      0.91      0.88      1036
           1       0.68      0.54      0.60       373

    accuracy                           0.81      1409
   macro avg       0.76      0.72      0.74      1409
weighted avg       0.80      0.81      0.80      1409

45/45 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step

=== Adam Optimizer ===
              precision    recall  f1-score   support

           0       0.84      0.90      0.87      1036
           1       0.66      0.53      0.59       373

    accuracy                           0.80      1409
   macro avg       0.75      0.71      0.73      1409
weighted avg       0.79      0.80      0.80      1409

45/45 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step

=== RMSprop Optimizer ===
              precision    recall  f1-score   support

           0       0.82      0.92      0.87      1036
           1       0.68      0.45      0.54       373

    accuracy                           0.80      1409
   macro avg       0.75      0.69      0.71      1409
weighted avg       0.78      0.80      0.78      1409

45/45 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step

=== Optimized (Optuna) ===
              precision    recall  f1-score   support

           0       0.84      0.90      0.87      1036
           1       0.66      0.53      0.59       373

    accuracy                           0.80      1409
   macro avg       0.75      0.72      0.73      1409
weighted avg       0.79      0.80      0.80      1409
```

```
# =====================
# Visualization
# =====================
plt.figure(figsize=(12, 6))
plt.plot(history.history['val_accuracy'], label='Baseline (SGD)')
```

```
plt.plot(history.history['val_accuracy'], label='Baseline (SGD)')
plt.plot(adam_history.history['val_accuracy'], label='Adam')
plt.plot(rmsprop_history.history['val_accuracy'], label='RMSprop')
plt.title('Validation Accuracy Across Optimizers')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```



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